A multiagent recommending system for shopping centres

Javier Bajo[1], Juan M. Corchado[2], Yanira de Paz[2], Juan F. de Paz[2], Quintín Martín[2]

Abstract. This paper presents a multiagent model that provides recommendations on leisure facilities and shopping on offer to the shopping mall users. The multiagent architecture incorporates deliberative agents that take decisions with the help of case-based planners. The system has been tested successfully, and the results obtained are presented in this paper.

1 INTRODUCTION

Multiagent systems have become increasingly relevant for developing applications in dynamic and flexible environments, such as the internet, personalized user interfaces, oceanography, control systems, recommendation systems or robotic [4, 9, 10]. Agents can be characterized through their capacities such as autonomy, reactivity, pro-activity, social abilities, reasoning, learning and mobility. These capacities can be modelled in various ways, using different methodologies. One of the possibilities is to use Case Based Reasoning (CBR) [1]. This paper presents a distributed architecture whose principal characteristic is the use of CBP-BDI recommender agents [11]. These deliberative agents incorporate a reasoning Case Based Planning (CBP) engine [13], a variant of CBR systems which allows the agents to learn from initial knowledge, interact autonomously with the environment and users, and allows it to adapt itself to environmental changes by means of discovering knowledge "know how". The aim of this work is to obtain a model for recommending plans in dynamic environments. The proposal has been used to develop a recommending system for the uses of a shopping mall, that helps them to identify bargains, offers, leisure activities, etc.

We have developed an open wireless system, capable of incorporating agents that can provide useful recommendations and services to the clients not only in a shopping centre, but also in any other environment such as the labor market, educational system, medical care, etc. Users are able to gain access to shopping and sales and leasing time information (entertainment, events, attractions, etc) by using their mobile phone or PDA. Mechanisms for route planning when a user wants to spend time in the mall are also available. Moreover, it provides a tool for advertising personalized offers (a commercial manager will be able to make his offers available to the shopping mall clients), and a communication system between directorship, commercial managers or shopping mall clients.

The Mall has become one of the most prevalent alternative to traditional shopping [3]. A shopping mall is a cluster of independent shops, planned and developed by one or several entities, with a common objective. The size, commercial mixture, common services and complementary activities developed are all in keeping with their surroundings [3]. Every shopping mall has a permanent image and a certain common management. Part of shopping mall management includes solving incidents or problems in a dynamic environment. As such, a mall can be seen as a large dynamic problem, in which the management required depends on the variability of the products, clients, opinions, etc [6].

In the next section, the wireless multiagent system developed will be presented, paying special attention to the Planner agent detailed in the third section. Finally, some preliminary results and conclusions are presented.

2 RECOMMENDING MULTIAGENT SYSTEM

Recommender systems have been widely studied and different artificial intelligence techniques have been applied. The application of agents and multiagent systems facilitates taking advantage of the agent capabilities, such as mobility, pro-activity or social abilities, as well as the possibility of solving problems in a distributed way. There are many architectures for constructing deliberative agents and many of them are based on the BDI model [7]. In the BDI model, the internal structure of an agent and its capacity to choose, is based on mental aptitudes. The method proposed in [13] facilitates the incorporation of CBR systems as a deliberative mechanism within BDI agents, allowing them to learn and adapt themselves, lending them a greater level of autonomy than pure BDI architecture [7]. The architecture proposed in this paper incorporates "lightweight" agents that can live in mobile devices, such as phones, PDAs, etc. [6, 9], so they support wireless communication (Wi-Fi, Bluetooth) which facilitates the portability to a wide range of devices [9].These agents make it possible for a client to interact with the MAS in a very simple way, downloading and installing a personal agent in his mobile phone or PDA. The system also incorporates one agent for each shop in the shopping mall. These agents can calculate the optimal promotions and services at a given moment. The core of the MAS is a Recommender agent that generates plans (routes) in response to a client's request, looking for the best shopping or leisure time alternatives. The agent has to take into account the client profile, the maximum amount of money that the client wants to spend and the time available. The route generation must be independent of the mall management, in the sense that it is not appropriate to use the same knowledge base (or all the knowledge) that the directorship controls. Only the knowledge corresponding to the offers and promotions at the moment of the recommendation should be used. Otherwise the client will be directed to the objectives of the shopping mall management. As can be seen in Figure 1 there are three types of agents: Recommender agent, Shop agents situated in each shop and User agents situated in the client mobile devices. Each User agent communicates to nearest shops and can communicate to the Recommender agent. Shop agents communicate to Recommender agent and User agents.

[1] Pontifical University of Salamanca, Spain, e-mail: jbajope@upsa.es
[2] University of Salamanca, Spain, e-mail: corchado@usal.es, yanira@usal.es, qmm@usal.es, fcofds@gmail.com

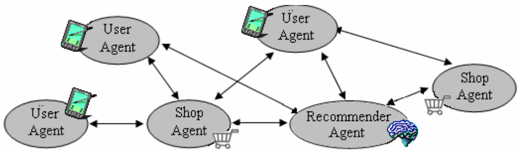

Figure 1. MAS: Coodinator agent, Shop agents and User agents.

The option chosen to define an appropriate analysis and design methodology for the problem to be resolved is one that combines Gaia [17] and AUML [2], in an attempt to take advantage of both [4]. Studying the requirements of the problem, three agent types have been chosen: The User Agent plays three roles, the Communicator role manages all the communications of a client; the Finder role looks for near devices and the Profile Manager role obtains a client profile. The Shop agent plays two roles, the Store Operator is in charge of manage the store (data base operations on stored products), moreover monitors the products shortage, in order to prevent desupply; and the Promotions Manager role controls the retails in each shop, as well as the promotions that every shop offers to its clients. Finally the Recommender agent plays four roles, the Clients Manager role deals with the client profiles management and controls the connected clients at a given moment; the Analyst role carries out periodic evaluations on retails, promotions and surveys data trying to provide a good quality service; the Incidents Manager role manages incidents, such as sending advices, or solving a wide range of problems; the Planner role is the most important role in our system. The Planner creates a route printing the most suitable shops, promotions or events to the client profile and available resources at one particular moment.

As far as interaction is concerned, the dependences and relationships between roles are described. Each interaction in which roles are involved requires protocols. In the SMA presented in this work the next protocols have been considered: RequestPromotionsData when the Recommender or a User agents ask about promotions data and a Shop agent sends the response, SolveConsult when the User agent makes query to a Shop agent and receives the response, AlertShortage is used for a Shop agent to inform the Recommender agent about a product shortage, InformOrderSupplier is used for a Shop agent to inform the Recommender agent about an order carrying out, InformProductsState when a Shop agent inform the Recommender agent about its products state, InformPromotionsState is used for a shop to send periodic information about promotions to the Recommender agent, SolveIncident is used for a Shop or User agent to indicate to the Recommender agent that an incident has happened and receive the response, SolveRecommendation when the User agent asks the Recommender agent about a plan and receives the response, finally Notify is used for the Recommender agent to send notices to User or Shop agents. For example, when a client asks for a new route, the user agent uses the SolveRecommendation protocol. The Recommender agent sends the recommendation and keeps receiving the results of each of the subgoals proposed. If necessary a replannig will be maid.

The case structure for a client profile shown in Table 1, is defined using CBML [11]. The structure is defined through feature labels. The items, attributes and their values and weights are labelled. In our problem three main attributes have been considered: personal data, retail/leisure time data and interests data. The retail/leisure attribute is composed of business type, business identification, product type, product identification, price, units and date attributes. The interests data attribute is composed of retail time and frequency, monthly expense both business and product, extracted from retail data, and the explicit attributes obtained from questionnaires. Each attribute has a value, noun or adjective, and an assigned weight. Since the number and type of business is high, the businesses were classified into leisure time (cinema and recreational), catering (restaurant, fast food and pizza) and public retail (clothes, shoes, computing, supermarket and optical). The products have been also classified, for example the films are divided in action, comedy, terror and drama.

Table 1. User profile case fields.

Case Field	Measurement
PERSONALDATA	Client Personal Data (ClientData)
RETAILDATA	Retails (RetailsData)
INTEREST	User interests (UserInterest)

The agent controlling recommendations is a CBP-BDI agent. This agent deals with multiple objectives derived from the tasks of coordinating all the shops, the client management and planning and optimization of routes. The routes and promotions proposed to a client consider the client profile and their resources (money and time) at the moment of the route request. It maintains a mall map and an estimation of the time employed walking by a client. The Recommender agent is able to generate routes, analyze retail and promotion data, manage incidents and manage clients at the same time. To solve the problem of route recommendation the Recommender agent uses an innovative planning mechanism: the Case Based Planning. CBP provides the agent with the capabilities of learning and adaptation to the dynamic environment. Moreover, the Recommender is able to apply a dynamic replanning technique, the MRPI (Most RePlan-able Intention), which allows the agent to change a plan at execution time when an incident happens [13]. The Recommender agent implements the reasoning cycle of the CBP system by means of three capabilities: Update, KBase and VCBP (Variational CBP) capabilities. The Update capability implements the retrieve (neural network based on principal component analysis and subsequent similitude algorithms) where the past experiences are retrieved and retain stages, while the KBase capability implements the reuse stage (neural network based on pondered weight technique [12]) and the revise stage VCBP capability , where the user opinion is evaluated. The VCBP capability also controls the dynamic replanning task.

The platform chosen for implementation was Jadex [16], a JADE add-on. The Jadex agents deal with the concepts of beliefs, goals and plans. A belief can be any type of java object and is stored in the beliefs base. A goal represents a motivation that has influence in the agent behaviour. A plan is a java procedure and is executed in order to achieve goals. Moreover all the JADE communication advantages are provided (even the LEAP add-on).

3 RECOMMENDER AGENT. CBP-BDI AGENT.

The purpose of case-based reasoning (CBR) is to solve new problems by adapting solutions that have been used to solve similar problems in the past [1]. The CBP is a variation of the CBR which is based on the plans generation from cases. The deliberative agents, proposed in the framework of this investigation, use this concept to gain autonomy and improve their recommending capabilities. The relationship between CBP systems and BDI agents can be established by implementing cases as beliefs, intentions and desires which lead to the resolution of the problem. As described in [13], in a CBP-BDI agent, each state is considered as a belief; the objective to be reached may also be a belief. The intentions are plans of actions that the agent has to carry out in order to achieve its objectives [7], so an intention is an ordered set of actions; each change from state to state is made after carrying out an action (the agent remembers the action carried out in the past, when it was in a specified state, and the subsequent result). A desire will be any of the final states reached in the past (if the agent has to deal with a situation, which is similar to a past one, it will try to achieve a similar result to that). Next, the CBP recommender is presented: Let $E = \{e_0,...,e_n\}$ the set of the possible interesting places to visit and buy. An Agent plan is the name given to a sequence of actions (1) that, from a current state e_0, defines the path of states through which the agent passes in order to offer to the client the better path according to each client's characteristics. Below, in (2), the dynamic relationship between the behaviour of the agent and the changes in the environment is modelled. The behaviour of agent A can be represented by its action function $a_A(t)\ \forall t$, defined as a correspondence between one moment in time t and the action selected by the agent.

$$a_j : \underset{e_i}{E} \ \underset{\rightarrow}{\rightarrow} \ \underset{a_j(e_i)=e_j}{E} \tag{1}$$

$$Agent\ A = \{a_A(t)\}_{t \in T \subseteq N} \tag{2}$$

From the definition of the action function $a_A(t)$ a new relationship that collects the idea of an agent's action plan can be defined. By knowing the action "a" that an agent A carries out at time t ($a_A(t)$), we have the plan that the agent carries out $p_A(t)$. . For each time t the agent A will carry out an action. These actions are functions and can be composed as such. To facilitate notation this composition of functions will be expressed as a sum in the discreet case and as an integral in the continuous case.

$$p_A(t_n) = \sum_{i=0}^{n} a_{iA}(t_i) \tag{3}$$

Where t_0 is the time of the agent's first action to be detailed and t_n the time of the last action. Given the dynamic character that we want to print onto our agent, the continuous extension of the previous expression (3) is proposed as a definition of the agent plan, in other words (4).

$$p_A(t_n) = \int_{t_0}^{t_n} a_A(t)dt \tag{4}$$

The variation of the agent plan $p_A(t)$ will be provoked essentially by: the changes that occur in the environment and that force the initial plan to be modified, and the knowledge from the success and failure of the plans that were used in the past, and which are favoured or punished via learning. O indicates the objectives of the agent and O' are the results achieved by the plan. R represents the total resources and R' are the resources consumed by the agent. The efficiency of the plan (5) is the relationship between the objectives attained and the resources consumed

$$E_{ff} = \frac{\#(O' \cap O)}{\#R'} \tag{5}$$

Where # means cardinal of a set. The objective is to introduce an architecture for a planning agent that behaves – and selects its actions – by considering the possibility that the changes in the environment block the plans in progress. This agent is called MRPI (most re-plan-able Intention agent) because it continually searches for the plan that can most easily be re-planned in the event of interruption. Given an initial point e_0, the term planning problem is used to describe the search for a way of reaching a final point $e_i \equiv e^* \in E$ that meets a series of requirements. Given a problem E and a plan $p(t)$ the functions Ob and Rc accumulated are constructed from the objectives and costs of the plan (6). For all time points t_i two variables are associated:

$$Ob(t_i) = \int_a^{t_i} O(t)dt \qquad Rc(t_i) = \int_a^{t_i} R(t)dt \tag{6}$$

This allows us to construct a space representing the environment for planning problems as a vectorial hyper dimensional space where each axis represents the accumulative variable associated with each objective and resource. The planning space, defined in this way, conforms to the following properties:

Property 1: The representations of the plans within the planning space are always monotonously growing functions. Given that $Ob(t)$ and $Rc(t)$ are functions defined as positive, function $p(t)$ expressed at these coordinates is constant or growing.

Property 2: In the planning space, the straight lines represent plans of constant efficiency. If the representations of the plans are straight lines, the slope of the function is constant, and coincides with the definition of the efficiency of the plan.

$$\frac{d}{dt}p(t) = cte \Leftrightarrow \lim_{\Delta \to 0} \frac{\Delta O(t)}{\Delta R(t)} = cte$$

In an n-dimensional space, the extension of the straight concept line is called a geodesic curve. In this sense, the notion of geodesic plans can be introduced, defined as those that maintain efficiency at a constant throughout their development, and therefore, they are the most replanned in the event of changes in the environment to be able to complete the desired objectives. This way, only the plans of constant efficiency (geodesic plans) are considered, due to the fact that they are the ones of minimum risk. If the efficiency is not constant it means that it depends on time, if the efficiency increases it means that there will be problems if the plan is interrupted quickly and if it decreases then there will be problems when the plan has almost concluded, in the sense that it has not found an alternative to obtain the objectives. As such, constant efficiency becomes increasingly important. In an environment that changes unpredictably, to consider any plan that is different from the geodesic plan means to accept a certain risk. The agent must search for the plan that determines a solution with a series of restrictions $F(O;R)=0$. In the plans base the plans sought are those that are initially compatible with the problem faced by the agent, with the requirements imposed on the solution according to the desires, and in the current state [1]. If all the possible plans $\{p_1,...,p_n\}$ are represented within the planning space, a subset of states that the agent has already attained in the past will be obtained in order to resolve similar problems. With the mesh of points obtained (generally irregular) within the planning space and using interpolation techniques, we can obtain the working hyperplan $h(x)$ (that encapsulates the information on the set of restrictions from restored experiences, by definition leading to a hyperplan since it verifies $h(x_j)=p_j\ j=1,...,n$ and the planning space is the dimension n). From this, geodesic plans can be calculated and and the variation calculation is applied. Suppose, for simplicity's sake, a planning space of dimension 3 with coordinates $\{O,R_1,R_2\}$. Between point e_0 and objective points $f_s f=\{e_1,..., e_m\}$ and over the interpolation surface $h(x)$, the Euler Theorem [13, 14] guarantees that the expression of the geodesic plans will be obtained by resolving the system of equations in (7), where R_i is the function accumulated R, O is the function of accumulated O and L is the distance function on the hyperplan $h(x)$, $L=\int_h dl$.

In order to obtain all the geodesic plans that, on the surface $h(x)$ and beginning at e_0, allows us to reach any of the points $e^* \in f_s f$, a condition of the surrounding must be imposed: the initial point will be $e_0=(O_0,R_0)$. Once an efficient plan is developed, the plans around it (along its trajectory) are used to create a denser distribution of geodesic plans. The tool that allows us to determine this is called the minimum Jacobi field associated with the solution set [15]. $g_0:[0,1]\rightarrow S$ be a geodesic over a surface S. Let $h:[0,1]\ x[-\varepsilon,\varepsilon]\rightarrow S$ be a variation of g_0 so that for each $t\ \epsilon\ (-\varepsilon,\varepsilon)$, the set $\{h_t(s)\}_{t\epsilon(-\varepsilon,\varepsilon)}$: $h_t(s)$ for all $t\epsilon(-\varepsilon,\varepsilon)$ are geodesic in S and they begin at $g_0(0)$, in other words, they conform to $h_t(0)=g_0(0)$ for all $t\epsilon(-\varepsilon,\varepsilon)$. In these conditions, taking the variations to a differential limit (8).

$$\begin{cases} \dfrac{\partial L}{\partial R_1} - \dfrac{d}{dO}\dfrac{\partial L}{\partial R_1'} = 0 \\ \dfrac{\partial L}{\partial R_2} - \dfrac{d}{dO}\dfrac{\partial L}{\partial R_2'} = 0 \end{cases} \tag{7}$$

$$\lim_{t\to 0}\{h_t(s) = g_0(s+t)\} = \lim_{t\to 0}\{h(s,t)\} = \frac{\partial g_0}{\partial t}\Big|_{(s,0)} = \frac{dg_0}{ds} \equiv J_{g_0}(s) \tag{8}$$

The term $J_{g0}(s)$ is given to the Jacobi Field of the geodesic g_0 for the set $\{g_n(x)\}_{n\epsilon N}$, and in the same way that the definition has been constructed, it is possible to give a measurement for the distribution of the other geodesics of $\{g_n(x)\}_{n\epsilon N}$ around g_0 throughout the trajectory. Given a set of geodesics, some of them are always g^* that, in their environment, have a greater distribution than other geodesics in a neighbouring environment. This is equivalent to saying that it presents a variation in the distribution of geodesics lower than the others and therefore the Jacobi Field associated with $\{g_n(x)\}_{n\epsilon N}$ reaches its lowest value at J_{g^*}. Let's return to the MRPI agent problem that, following the recuperation and variation calculation phase, contains a set of geodesic plans $\{p_1,...,p_n\}$. If the p^* is selected with a minimum Jacobi Field value, it can be guaranteed that in the event of interruption it will have around it a greater number of geodesic plans in order to continue. This suggests that given a problem with certain restrictions $F(O;R)=0$, the geodesic plan p^* with minimum associated Jacobi field associated with the set $\{g_n(x)\}_{n\epsilon N}$ is called the most re-plan-able solution. The behaviour model G for the MRPI agent is (9).

$$G(e_0, p_1, \cdots, p_n) = p^* \Leftrightarrow \exists n \in N / J_{g_n} \equiv J_{g^*} = \underset{n\in N}{Min} J_{g_n} \tag{9}$$

If the plan p^* is not interrupted, the agent will reach a desired state $e_j \equiv e^* \epsilon\ f_s f,\ j\epsilon\{1,...,m\}$. In the learning phase, a weighting $w_f(p)$ is stored. With the updating of weighting $w_f(p^*)$, the planning cycle of the CBP motor is completed. In Figure 3, it is possible to see what happens if p^* is interrupted. Let's suppose that the agent has initiated a plan p^* but at a moment $t>t_0$, the plan is interrupted due to a change in the environment. The geodesic planning meets the conditions of the Bellman Principle of Optimality [5], in other words, each one of the plan's parts is partially geodesic between the selected points. This guarantees that if g_0 is geodesic for interrupted e_0 in t_1, because e_0 changes to e_1, and g_1 is geodesic to e_1 that is begun in the state where g_0 has been interrupted, it follows that: $g = g_0 + g_1$ is geodesic to $e= e_0\ (t_1 - t_0) + e_1\ (t_2 - t_1)$

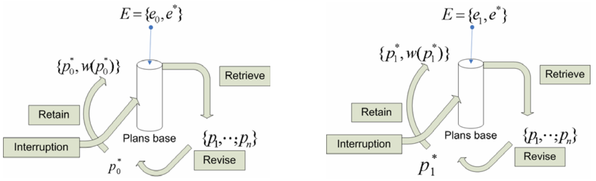

Figure 3. Model for behaviour G(t).

The dynamic process follows the CBP cycle recurrently: each time a plan finds itself interrupted, it generates the surroundings of the plans from the case base from the state reached so far, and adjusts them to the new problem. With this it calculates the geodesic plans and selects the one which meets the minimum conditions of the associated Jacobi field. In this way the dynamic planning model of the agent $G(t)$ is characterised as shown in Figure 3. A minimum global Jacobi field $J(t)$ also meets Bellman's conditions of optimality [5], in other words, a minimum global Jacobi field, must select minimum Jacobi fields "in pieces" (10). If on the one hand, successive Jacobi fields generate one Jacobi field, and on the other hand, minimum Jacobi fields generate a minimum Jacobi field, the MRPI agent that follows a strategy of replanning $G(t)$ as indicated to survive a dynamic environment, generates a global plan $p^*(t)$ that, faced with all possible global plans $\{p_n(t)\}_{n\epsilon N}$, presents a minimum value in its Jacobi field $J_{g^*}(t) \equiv J_{p^*}(t)$. An agent has been formally defined that in a dynamic environment seeks plans that lend it greater capacity for replanning.

$$J_{\min}(t) = \{J_{\min}(t_1 - t_0), J_{\min}(t_2 - t_1), \cdots, J_{\min}(t_n - t_{n-1})\} \tag{10}$$

Figure 4 shows a simple example: The mall main entrance has been taken as the origin of coordinates. Different positions (user, shops, leisure areas) are represented by means of coordinates in a plane (R^2). Bearing in mind the user's interests, places to visit are selected, then, the routes that include these points are traced, and the route most easily replanned in the event of interruption of the initial plans is proposed; this is done bearing in mind the time available, the shopping time and leisure activities schedule. The chosen route is surrounded by the greatest density of alternative routes, thereby ensuring the success of the proposed plan.

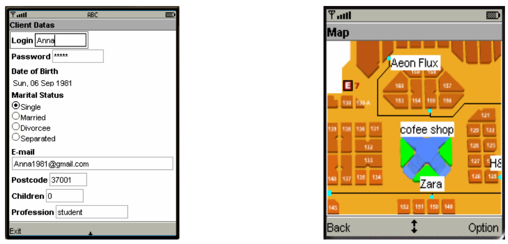

Figure 4. Screen shots for user profile and inform route.

4 RESULTS AND CONCLUSIONS

The system was tested at the Tormes Shopping Mall in the city of Salamanca during 2005 and 2006. The multiagent system has been tuned and updated, and although the system is not fully operational and the aim of the project is to construct a research prototype and not a commercial tool, the initial results have been very successful from the technical and scientific point of view. The construction of the distributed system has been relatively easy, using previously developed CBR-BDI libraries [4, 9, 10]. AUML [2] and Gaia [17] provide an adequate framework for the analysis and design. The formalism defined in [13] facilitates the straight mapping between the agent definition and the CBR construction. Figure 4 presents two screen shots of the User agent. It shows the form for introducing personal data and the route generated for a client trying to buy clothes and see an action movie. The security problem was tackled by using the FIPA https protocol and a private network to connect Shop agents with the Recommender agent.

The fundamental concept when working with a CBR system is the concept of case, so it is necessary to establish a case definition. A case managed by the Recommender agent, is composed of the attributes described in Table 2. Cases can be manipulated manually or automatically by the agent (during its revision stage, when the user evaluation obtained through questionnaires is given to the system). The agent plans can be generated using different strategies since the agent integrates different algorithms. The metrics mechanisms proposed in [8] facilitates the retrieval stage, but the products base and the promotions base must be defined and sorted including metrics that facilitate searches for similitude, for example the time expected for buying each product. The client profile is obtained from retail data and periodic questionnaires. The system has been tested from October 2005 to February 2006 obtaining promising results. The e-commerce techniques [3] have facilitated the client motivation since a user can easily find the products he/she is interested in, spend his leisure time in a more efficient way and make contact with other clients with whom he/she can share hobbies or opinions. So the degree of client satisfaction has been improved as observed in the surveys.

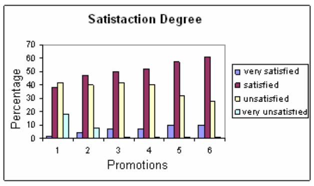

Figure 5. Clients satisfaction degree.

The first autonomous prototype started to work in October 2005 with a test set of 30 users, with up to 75 that gave their evaluations in the final promotions and a final number of different users of 157 with 328 evaluations, at least 50% of users giving an evaluation more than once. The users were selected among clients with a terminal supporting the application (Wi-Fi, Bluetooth). The results obtained show that the greater part of users, near 67%, were people aged between 16 and 30 years old, while the percentage of people older than 40 is less than 3%. However there were no significative differences with respect to client sex. Figure 5 shows the clients degree of satisfaction during the 6 promotions studied. The tendency indicates that as promotions were launched, the client satisfaction degree grew. As expected, at the beginning, the system obtains a low evaluation, basically due to the causes derived from the system start up; but as more cases were incorporated, the promoted products were closer to the user profile. Users have noticed the utility of the dynamic replanning, since it is quite usual for them to change opinions/objetives in the middle of a plan. The MRPI tool is greatly appreciated and optimizes the time spent in the shopping mall.

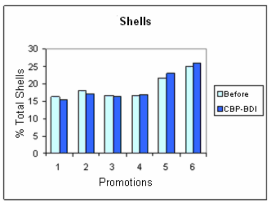

Figure 6. Retail promotional products and retail total products.

Table 2. Recommendation case fields.

Case Field	Measurement
CLIENT	Client profile (ClientProfile)
MONEY	Money to spend (Money)
TIME	Time (Time)
INIT	User initial location (Location)
PREF	User preferences (Preference)
SOLUTION	Solution and efficiency (Solution)

The percentage of sales of promotional products, shown in Figure 6, has slightly grown over the total. The basic reason is that clients have instant information about the products they are interested in, and the information is very accurate and customized.
As the system obtained more information about client profiles, products and habits, the system knowledge increases and the recommender agent provides more optimal plans. The clients also needed time to get used to the system.

ACKNOWLEDGEMENTS

This work has been supported by the Spanish Council for Research and Technology (MCYT) project and the JCyL Project JCYL-2002-05-SA104A05.

REFERENCES

[1] A. Aamodt and E. Plaza (1994) *Case-Based Reasoning: foundational Issues, Methodological Variations, and System Approaches*, AICOM. Vol. 7., March, pp 39-59.

[2] AUML www.auml.org

[3] F.G. Adams (2003): *The E-Business Revolution & the New Economy: E-conomics after the Dot-Com Crash.* South-Western Educational Pub.

[4] J. Bajo and J.M. Corchado (2005) *Evaluation and monitoring of the air-sea interaction using a CBR-Agents approach* Proccedings of the 6th Internacional Conference on Case-based Reasoning, ICCBR'05, LNAI pp. 50-62. Springer Verlag.

[5] R.E. Bellman (1957). *Dynamic Programming.* Princeton University Press, Princeton, New Jersey.

[6] T. Bohnenberger, O. Jacobs and A. Jameson (2005). DTP meets user requirements: Enhancements and studies of an intelligent shopping guide. *Proceedings of the Third International Conference on Pervasive Computing (PERVASIVE-05)*, Munich, Germany.

[7] M.E. Bratman, D. Israel, and M.E. Pollack (1988). *Plans and resource-bounded practical reasoning*. Computational Intelligence, 4, 349-355.

[8] R. Burke. *Knowledge-based Recommender Systems*. Encyclopedia of Library & Information Systems, 69(32), 2000.

[9] J.M. Corchado, E. Corchado y M.A. Pellicer (2004). *Design of cooperative agents for mobile devices*. Proceedings of the International Conference on Cooperative Design, Visualization and Engineering - CDVE2004. Luo Y. (Ed.) LNCS 3190, Springer Verlag. ISSN 0302-9743. ISBN 3-540-23149-8 pag. 205-212.

[10] J.M. Corchado, J. Pavón, E. Corchado and L.F. Castillo (2005) *Development of CBR-BDI Agents: A Tourist Guide Application*. 7th European Conference on Case-based Reasoning 2004. Lecture Notes in Artificial Intelligence 3155, Springer Verlag. pp. 547-559.

[11] L. Coyle, P. Cunningham and C. Hayes (2002). Representing Cases for CBR in XML. *Proceedings of 7th UKCBR Workshop*, Peterhouse, Cambridge, UK.

[12] Y. De Paz Santana (2005) *Mixture Weibull distribution using artificial neural networks with csnsurated data* PHD thesis, chapter 3.

[13] M. Glez-Bedia M, J.M. Corchado, E. Corchado and C. Fyfe (2002) *Analytical Model for Constructing Deliberative Agents*, Engineering Intelligent Systems, Vol 3: pp. 173-185.

[14] J. Jost and X. Li-Jost (1998). *Calculus of variations*. Cambridge University Press, U.K.

[15] J.M. Lee (1997). *Riemannian Manifolds. An introduction to Curvature*. Springer-Verlag, New Tork, Inc.

[16] A. Pokahr, L. Braubach, and W. Lamersdorf (2003) *Jadex: Implementing a BDI-Infrastructure for JADE Agents*, in: EXP - In Search of Innovation (Special Issue on JADE), Vol 3, Nr. 3, Telecom Italia Lab, Turin, Italy, September 2003, pp. 76-85.

[17] M. Wooldridge and N.R. Jennings and D. Kinny (2000) The Gaia Methodology for Agent-Oriented Analysis and Design. Journal of Autonomous Agents and Multi-Agent Systems, 3 (3). pp. 285-312.